Agent-based Modeling of Interaction between Commercial Building Stocks and Power Grid

Fei Zhao[#,*1], Jianhui Wang[#2], Vladimir Koritarov[#3], Godfried Augenbroe[*4]
[#]Decision and Information Sciences Division, Argonne National Laboratory, Argonne, IL
[*]College of Architecture, Georgia Institute of Technology, Atlanta, GA
[1]feizhao@gatech.edu, [2]jianhui.wang@anl.gov,
[3]Koritarov@anl.gov, [4]Godfried.Augenbroe@coa.gatech.edu

Abstract — *This paper describes a preliminary study on simulating commercial buildings modeled as consumer agents that interact with the power grid. A simple hourly bottom-up building energy model is developed with respect to climate conditions and building design and operation. This model is used to simulate different types of commercial buildings as agents and to derive the hourly load profile of the entire building stock at the city/regional level. By updating building operating parameters in this bottom-up model according to different occupant control strategies under real-time electricity pricing, the total electricity demand of the building stock can be estimated; this will, in turn, affect the electricity market. Two test cases are modeled to estimate the commercial building stock demand response and its impact on the regional electricity market.*

I. INTRODUCTION

In the United States, commercial and residential buildings account for 39% of primary energy consumption, 40% of carbon dioxide emissions, 71% of electricity use, and 54% of natural gas use [1]. Energy use for buildings steadily increased from 1985 to 2000 by 17% and is projected to grow annually by 1.7% to 2025 [2]. Lighting, HVAC (heating, ventilation, and air conditioning), and appliances account for a big fraction of energy consumption. Studies have shown that commercial buildings have equipment and operational deficiencies that lead to wasting up to 20% of energy used for HVAC, lighting, and refrigeration as a result of problems with system operation [3]. Utility demand response programs give consumers a role in managing their energy use on the basis of the cost of power at any given time. A recent study conducted by the Federal Energy Regulatory Commission (FERC) estimated that if price-responsive programs were universally added to the mix of existing load demand programs in the United States, a reduction of 20% in peak demand could be achieved by the year 2019 [4].

To simulate the interplay of different players (regulators, generation companies, transmission companies, distribution companies, and consumers), an agent-based modeling paradigm has been advocated as both a solution and a framework for analyzing the properties of systems in which multiple self-interested parties interact [5-7]. Much research has focused on attempting to simulate the electricity price elasticity and consequences of implementing demand response programs in a real-time pricing market. In these studies, electricity consumers (i.e., buildings) are usually modeled as predefined, aggregated, and fixed-load profiles on the basis of historic regional electricity consumption data. Such a simplified model focuses on the electricity generation and transmission levels but cannot model the diversity and dynamics of building consumers in terms of design and operation.

In this paper, we address this shortcoming and provide an agent-based framework for modeling the dynamic response of the commercial building stock in a real-time pricing market. In this framework, a cluster of buildings of the same type (a total of 10 types are considered in this study) located in the same city/region is considered to be an agent. The electricity demand of the building agents is determined by running a simple hourly physical energy simulation for representative buildings in the stock and scaling it to the entire agent cluster by building floor area. Sets of input parameters for the representative buildings are developed with respect to building type, location, and age. By using this framework under certain assumptions and given the general information on building design and operation, we can predict the hourly total electricity demand of a building stock. In addition, by updating the input parameters of the physical building model, we can also quantify the consequences of building load reduction behaviors. In more detail, this work advances the state of art in the following ways:

1. We developed a simple hourly building end-use energy modeling program based on ISO 13790 [8]. Given climate conditions and general specifications for the building program, materiality, HVAC, and equipment, the model can calculate building load profiles while requiring very little computing intensity. Comparisons between this model and EnergyPlus [9] for different commercial building types showed overall compliance. Meanwhile, we also noticed that a deeper comparison study that would improve this research

in future is to compare the detailed simulation and normative calculation on the basis of what can be known out of the cluster of buildings we are considering, when we do not know enough information about them. A probabilistic view of demonstrating estimation accuracy with uncertainty gives more information for decision makings.

2. We provided a building stock modeling framework in the domain of power grid modeling, so that commercial buildings can be modeled in more detail with regard to their composition and operation.

3. Using our agent-based framework in a real-time pricing market, we can show how much utility cost can be saved by adjusting building operating parameters (air-conditioning set-point temperature, lighting intensity, etc.). If we apply this framework to a larger region, the impact on the local electricity price can also be modeled on the basis of the electricity supply curve. In short, this is the first attempt at applying hourly building energy models to a large-scale electricity supply simulation.

The rest of the paper is structured as follows. Section II introduces the bottom-up simple hourly building energy model. Section III extends the single building model to commercial building stock agents, considering different building types. Section IV combines the electricity demand of these agents with the supply curve and shows example experiments. Section V has the conclusions.

II. Bottom-up Building Energy Model

Simple Hourly Building Energy Model

Several models and tools have been developed to evaluate energy use and the indoor environment conditions in commercial buildings. They range from simplified normative procedures useful for hand calculations to dynamic simulation models that use detailed numerical calculations of heat, air, and moisture transfer by sophisticated systems that control temperature, daylight, etc. The simplified calculation procedures often use only a few items of input data and a limited set of equations to maintain a high level of transparency, reproducibility, and robustness. Major benefits of using the normative model include (1) reducing input parameters as much as possible; (2) making modifications to the input parameters easy by directly using the physical behavior to be implemented; and (3) maintaining an adequate level of accuracy, especially for air conditioned buildings where the thermal dynamic of the room behavior has a high impact.

The present effort uses the existing ISO 13790 [8] simple hourly approach as a starting point before estimating the building hourly electricity demand. It is based on an equivalent resistance-capacitance (R-C) network, as shown in Fig. 1.

In this model, the input parameters include building geometry (floor area, elevation, and window-wall ratio), materiality (U-value, light transmission, and absorption factors of enclosure), HVAC (schedule, efficiencies, and set-point temperature), and lighting and equipment (intensity and schedule). Typical meteorological year (TMY) hourly weather data are also used. Then the heating and/or cooling needs are found by calculating, for each hour, the heating or cooling power ($\varphi_{HC,nd}$) that needs to be supplied to or extracted from the indoor air node (θ_{air}) to maintain a certain set-point indoor air temperature.

Heat transfer by ventilation (H_{ve}) is connected with the supply air temperature (θ_{sup}) and the interior temperature (θ_{int}). Heat transfer by transmission is split into the window part ($H_{tr,w}$) and non-window part ($H_{tr,em}$ and $H_{tr,ms}$); only the non-window part is connected by a single thermal capacity (C_m), representing the building thermal mass. The heat gains from internal and solar sources are split into three parts (φ_{air}, φ_s and φ_m) and applied to the nodes of indoor air (θ_{air}), internal environment (θ_s), and thermal mass (θ_m), respectively.

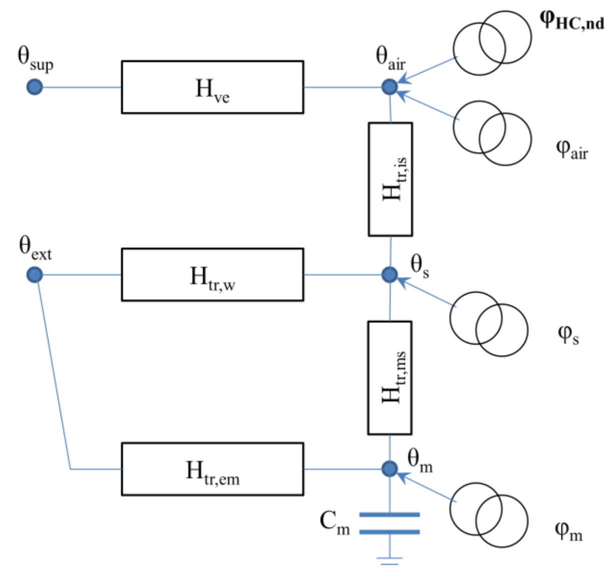


Figure 1. Thermal R-C model of the simple hourly method

The detailed calculation procedure is described in ISO 13790. Validation of the simple hourly method at the thermal need level was also performed against detailed dynamic simulations [10, 11].

On the basis of the calculated thermal needs, we developed modules to estimate the hourly end-use energy for heating, cooling, lighting (interior and exterior), equipment (interior and exterior), refrigeration, fan, and pump according to the building design and operation specifications. These categories were then summed up to get the total end-use consumption of electricity and natural gas.

Testing and Validation

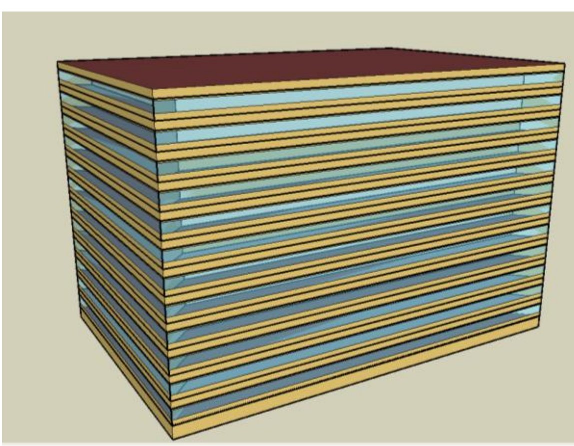
In order to estimate the electricity consumption of the actual commercial building stock, the building energy model should be able to estimate the energy consumption of different building types. The 2003 Commercial Building Energy Consumption Survey (CBECS) [12] provides a list of commercial building types and their surveyed energy consumption data. We selected the 10 types listed in Table I from it. CBECS data show that these 10 types cover 83.7% of the U.S. total electricity consumption of commercial buildings. Other building types (e.g., public assembly, religious worship, vacant) have different energy consumption patterns and cannot be simply modeled. Because of their small share in the national electricity consumption, they are ignored in this study.

TABLE I. CONSIDERED BUILDING TYPES

Abbrev.	Building Type	2003 Electricity Consumption (kWh)	% of CBECS Total
O	Office	211	20.2
S	Supermarket	153*	14.7
M	Strip Mall		
E	Education	109	10.5
H	Healthcare	73	7.0
W	Warehouse and Storage	72	6.9
L	Lodging	69	6.6
FE	Food Service	63	6.0
R	Retail (Other Than mall)	62	5.9
FS	Food Sales	61	5.8
Total		873	83.7
* Classified as "Enclosed and strip mall" in CBECS 2003.			

The U.S. Department of Energy (DOE), in conjunction with three of its national laboratories, developed commercial reference buildings, formerly known as commercial building benchmark models [13]. These reference buildings provide complete descriptions for conducting whole building energy analysis using EnergyPlus simulation software [9], a dynamic building energy simulation tool developed by DOE. The proposed simple hourly model is compared with EnergyPlus. We modeled the representative buildings of the above 10 types in the proposed model to compare the seasonal and diurnal electricity demand profiles with EnergyPlus results.

Take the office building as an example. The reference office design in Fig. 2 is selected as an existing building built after 1980. This rectangular office in Chicago, Illinois, has 12 floors and a total floor area of 46,320 m^2. Its primary heating source is natural gas.



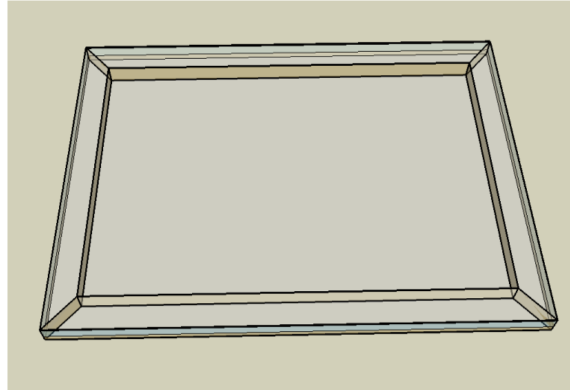


Figure 2. Reference office building in perspective and plan

The annual total electricity results are broken down into different building energy categories as shown in Fig. 3. The data on consumption for cooling, lighting, and equipment from the simple hourly model are very close to the results simulated by EnergyPlus. However, the simple hourly model has a larger error for the consumption by fans and pumps (32% less) and heat rejection (not considered). Overall, the annual total electricity consumption calculated by the simple hourly model is only 2% less than the results from EnergyPlus.

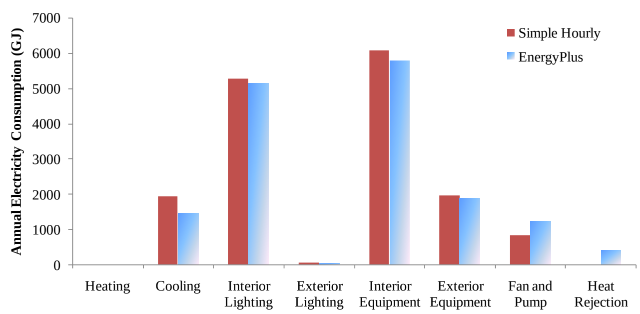


Figure 3. Annual electricity consumption breakdown calculated by EnergyPlus and the simple hourly model

Fig. 4 compares the hourly electricity demand over a year calculated by EnergyPlus and by the proposed simple hourly model. There is a peak demand during summer because of the high cooling load. In winter, the daily load patterns remain relatively regular because the test building uses natural gas as the source for heating. The comparison shows an overall compliance between the results of the two methods. However, the simple hourly model underestimates the daily peak load during the intermediate seasons (Apr–Jun and Oct–Nov) by up to 20%. Moreover, it overestimates the daily peak load during Jul–Aug by up to 30%. The differences are mainly a result of the oversimplification of multi-zone dynamic simulation when compared with EnergyPlus. During the intermediate seasons, within the time step co-existing heating and cooling loads in different air-conditioning zones of the building offset each other and give a lower estimate of total demand in the simple hourly model.

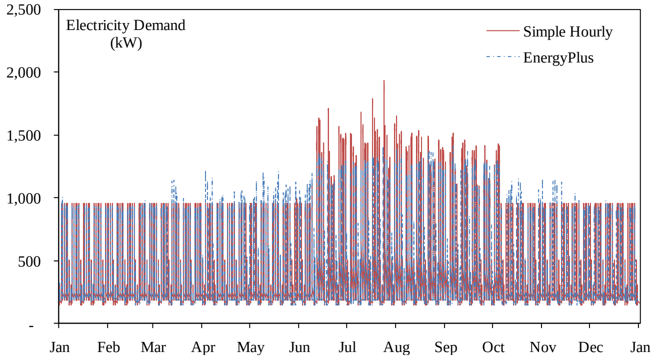


Figure 4. Hourly electricity demand of the reference office building calculated by EnergyPlus and the simple hourly model

The hourly electricity demand for the test building for two typical weeks in January and August are plotted in Fig. 5 and Fig. 6. The profiles calculated by the two methods resemble each other well in winter, when there is no cooling demand. In summer, the daily peak demands are slightly different in the two models. In summer, the difference is around 10% for weekdays, and up to 50% for weekends.

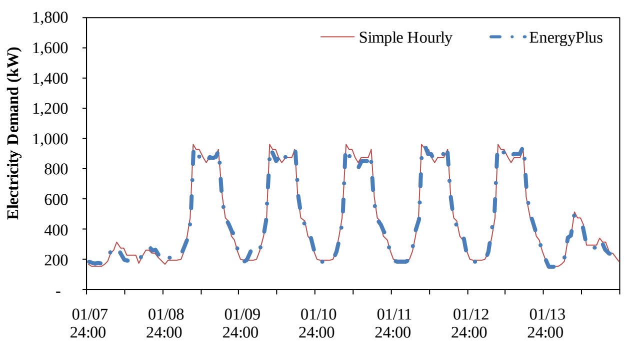


Figure 5. Hourly electricity demand, January 7th through 14th

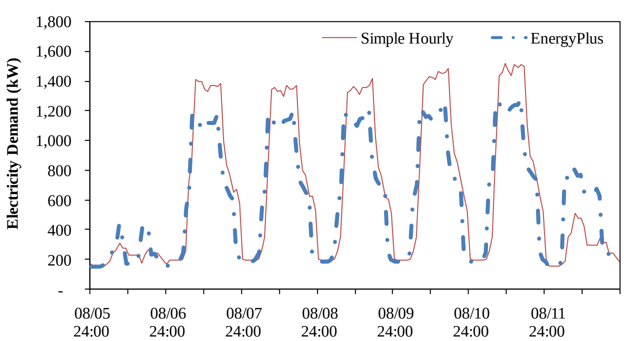


Figure 6. Hourly electricity demand, August 5th through 12th

The comparison of yearly and daily electricity demand profiles shows that the proposed simple hourly model gives a reliable estimate of the annual total demand as well as of diurnal variation for most of the time.

We performed testing and validation of all the building types listed previously. In general, an estimation error exists, but it is acceptable for the large-scale building stock energy calculation. These tests and validations provide the foundation for the commercial building stock modeling. The simple hourly building models are used as the core of the commercial building agents.

III. Commercial Building Stock Agents

Broadly, there are two fundamental methods for modeling energy consumption from a certain amount of buildings at the city/regional/national level: the top-down approach and bottom-up approach [14, 15]. The physically based bottom-up approach takes into account information on building design and operations. This "white-box" approach is thus more flexible in simulating the consequences of changes to building operations than the "black-box" top-down statistical models. Typically the bottom-up building stock energy simulation consists of the following steps:

1) Categorizing the whole building stock according to energy consumption characteristics;
2) Designing building prototypes, each representing a building stock category that is used as an input dataset for simulation in the next step;
3) Performing simulations by using these prototypical building models to predict the energy consumption per unit floor area or household in each building stock category as an agent; and
4) Aggregating the total energy consumption by summing up the predicted energy consumption of all building stock categories.

This modeling approach has been applied and advanced in several studies [15, 16]. The purpose of these studies is usually to estimate the baseline and improved annual/monthly energy demand of the building stock in order to advance design improvements and policy making. However, very little work has been done on the application of hourly based modeling to simulate the dynamic interaction between the building stock and the electricity grid. This type of large-scale simulation requires a good balance between the required calculation accuracy and computing intensity. Apparently either the over-engineering and detailed simulation model, or the overwhelming amount of buildings modeled in a stock, would not meet this requirement.

The framework we are proposing considers a cluster of buildings of the same type within the same region to be one agent. The hourly electricity demand of this agent is determined by multiplying the total floor area of this building type in this region to the electricity use intensity (in MW/m^2) of its representative design, calculated by the simple hourly method. The validity of this simplification is going to be studied, in the light of the sensitivity of the decision making on the outcome of the simulation. This not only relates to the aggregation but also to the chosen simulation method.

Each region/city may have multiple commercial building agents. Different weather profiles apply to agents in different regions. Fig. 7 illustrates the relationship between building agents, region/city, and transmission lines. The letters in the circles are abbreviations of building types, listed in Table I.

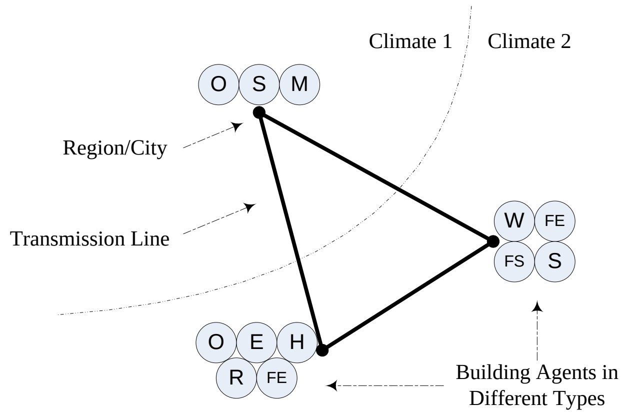


Figure 7. Conceptual relationship between building agents, regions, and transmission lines

Each building agent requires a list of input parameters to be specified, as shown in Table II. These parameters are classified into program, materiality, HVAC, and equipment.

TABLE II. REQUIRED INPUT PARAMETERS FOR EACH BUILDING AGENT

Program	Materiality
Building location Total conditioned floor area Building height Opaque wall area (all directions) Window area (all directions) Occupancy	U-value of envelope Solar transmittance Solar Heat Gain Coefficient (SHGC) of glazing Reflectance of opaque walls Solar shading factor of glazing Building thermal inertia
HVAC	**Equipment**
Ventilation needs and schedule Thermostat set-point temperature Heating energy source H/C generation efficiency H/C distribution efficiency Fan and pump size and schedule	Int. lighting intensity and schedule Ext. lighting intensity and schedule Int. equipment intensity and schedule Ext. equipment intensity and schedule Refrigeration capacity and schedule

The input parameters of the representative designs are crucial to the simulation results. If local data are available, the accuracy can be improved by dividing the interested area into multiple small regions and specifying local average data for each building agent. However, in most cases, when local building data are not available, regional statistical data are used instead. Ref. [17] studied the ranges of energy modeling input parameters for commercial buildings by building type in different climate zones and checked the simulation results against CBECS 2003. We adapted these results and developed a prototype for Illinois as an example.

We used the same geometry of DOE commercial reference buildings in the prototype. The set of parameters of materiality, HVAC, and equipment are classified as Old Vintage (pre-1980) and New Vintage (post-1980), according to the construction or renovation time of the majority of the buildings in the stock. The user of the tool is able to select the class that best describes the real condition, and then the corresponding set of input parameters are applied to the agent. With supermarkets as an example, the set of materiality parameters for Illinois is listed in Table III.

TABLE III. REPRESENTATIVE MATERIALITY INPUT PARAMETERS FOR SUPERMARKETS

Category	Parameter (Unit)	Pre-1980	Post-1980
Materiality	Wall U-value (W/m^2/K)	1.721	0.979
	Roof U-value (W/m^2/K)	0.617	0.494
	Wall reflectance	0.08	0.08
	Window SHGC	0.407	0.385
	Bldg. thermal inertia (1 very light, 5 very heavy)	4	3

Complete sets of input parameters for each representative building with respect to climate zone and building age is stored in a database. When the total floor area, building age (pre- or post-1980), and primary heating source (electricity or non-electricity) are specified for each building agent, the software selects the corresponding input files from the representative building parameter database and the right climate data from the climate database. Input data files then go to the simple hourly model. The calculated hourly electricity demands of building agents are then aggregated to derive the total hourly demand profile of the region. Given the demand profile and a power supply curve, the electricity price can then be determined and inform building operations as a feedback. This calculation process is illustrated in Fig. 8.

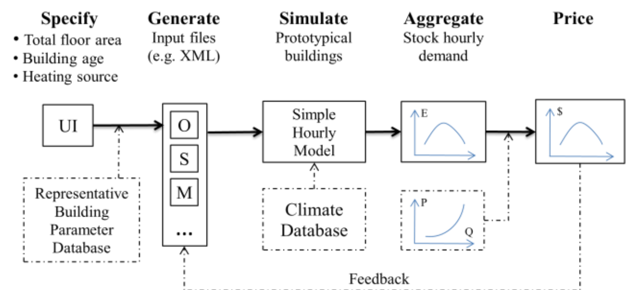


Figure 8. Agent-based building stock energy simulation process

IV. INTERACTION BETWEEN COMMERCIAL BUILDING STOCK AND THE POWER GRID

In this proposed framework, since building agents are based on bottom-up physical models, building operation behavior can be connected with the price aspects of the power market.

First, building agent input parameters can be dynamically manipulated to reflect the reactions of building operation (e.g., change A/C set-point temperature, reduce lighting intensity) to the electricity price. This quantifies the amount of utility savings to the agents in a typical local climate condition. Second, also shown in Fig. 8, in a real-time pricing electricity market, the hourly electricity price can be determined by the building stock load profile and a power supply curve. This demand response process is also modeled in the prototype. This section shows two experiments to demonstrate these scenarios.

Test Case 1: Load Reduction

We use a simple building stock consisting of only office buildings to demonstrate the demand reduction. Specifications of the building agent in this test case are shown in Table IV.

TABLE IV. BUILDING STOCK SPECIFICATION IN CASE 1

Building Type	Total Floor Area (million sq. m)	Dominant Building Age	Primary Heating Source
Office	1	Pre-1980	Natural gas

This building stock is located in Chicago. A typical hourly electricity price profile in Illinois is assigned to the agent (Fig. 9). It is assumed that the electricity demand of this agent has little impact on the electricity price.

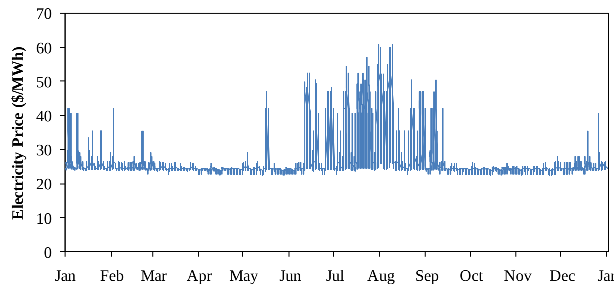


Figure 9. Typical hourly electricity price profile

In this market, given the electricity price in the previous hour, it is assumed buildings can take three demand-reducing actions (Table V). When the price is above $45/MWh, the indoor AC set-point increases by 2°C. When the price is above $50/MWh and $55/MWh, lighting and internal equipment power, respectively, decrease by 20%.

TABLE V. AGENT LOAD-REDUCING ACTIONS AND ELECTRICITY PRICE

Demand Reduction Scenario	When the Power Price Is above	Action from Buildings
Cooling set-point	$45/MWh	Increase set-point temp. by 2°C
Lighting	$50/MWh	Reduce lighting load by 20%
Internal equipment	$55/MWh	Reduce load by 20%

On the basis of TMY climate data and stock specifications, the prototype simulates hourly stock electricity demand and price for a year. Fig. 10 compares the baseline (no action) and reduced loads simulated for the week of August 4. At noon of each business day when the electricity price approaches the daily peak, three load reduction scenarios are activated to reduce the power demand. The corresponding hourly electricity cost is also plotted in Fig. 11.

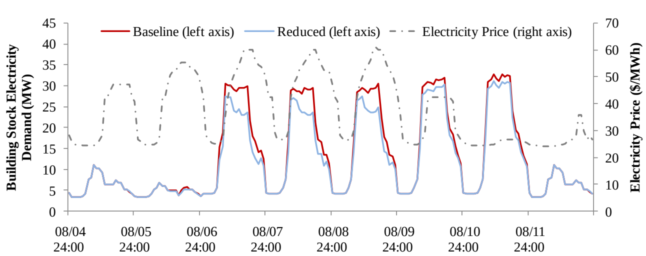


Figure 10. Office agent electricity demand profile before and after three reduction actions, Aug. 4th through 12th

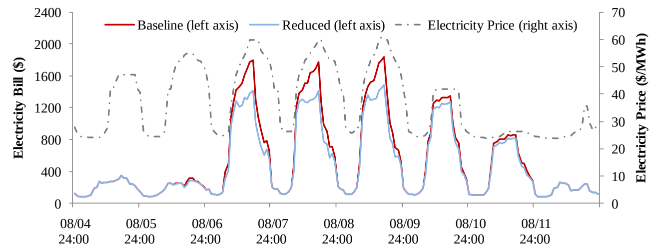


Figure 11. Office agent electricity bill profile before and after three reduction actions, Aug. 4th through 12th

To quantify the effectiveness of the different load reduction scenarios, the annual electricity conservation and utility savings are aggregated (Table VI). In this test case, reductions in lighting and internal equipment power have very little impact with regard to saving energy and money because of the higher thresholds and small reduction percentages for these two scenarios. But increasing the 2°C cooling set-point temperature at an electricity price of $45/MWh or above leads to a 2.83% annual electricity reduction and 3.41% monetary savings.

TABLE VI. UTILITY SAVINGS OF THE DEMAND REDUCTION ACTIONS FOR THE TEST BUILDING STOCK

Demand Reduction Scenario	Annual Electricity Reduced (MWh | %)		Annual Monitory Saving ($ | %)	
(a) Cooling set-point temp.	2,733	2.83%	93,707	3.41%
(b) Lighting	231	0.24%	12,163	0.44%
(c) Internal equipment	44	0.05%	2,549	0.09%
(a), (b), and (c)	3,009	3.11%	108,418	3.95%

Test Case 2: Grid Reaction

Test Case 1 showed an example of estimating energy and monetary savings of load reduction when the electricity price profile is fixed. If we consider a city/state-scale network in the real-time electricity market, the electricity price can also change when buildings reduce their peak loads. A much larger building stock with a combination of different building types (Table VII) is modeled in this test case. The relative proportion of each type is estimated according to the CBECS 2003 building characteristics summary for the Midwest U.S.

TABLE VII. BUILDING STOCK SPECIFICATION IN TEST CASE 2

Building Type	Total Floor Area (million sq. m)	Dominant Building Age	Primary Heating Source
Office	108	Pre-1980	Natural gas
Supermarket	14	Post-1980	Natural gas
Strip Mall	11	Post-1980	Electricity
Education	92	Pre-1980	Natural gas
Healthcare	29	Post-1980	Natural gas
Warehouse and Storage	109	Post-1980	Natural gas
Lodging	41	Pre-1980	Electricity
Food Service	16	Post-1980	Natural gas
Retail (other than mall)	32	Post-1980	Natural gas
Food Sales	12	Post-1980	Natural gas

We consider a macro-model of the electricity market, a black box that abstracts the market mechanism and trading, and the transmission power flow security involved in an actual electricity market. Given the characteristics of the market, our prototype gives the market prices based on the economics of supply and demand, shown in Fig. 12. The supply curve is generated from the capacity of the local generation companies. In each hour, the electricity price is determined by this supply curve and the total electricity demand of the previous hour.

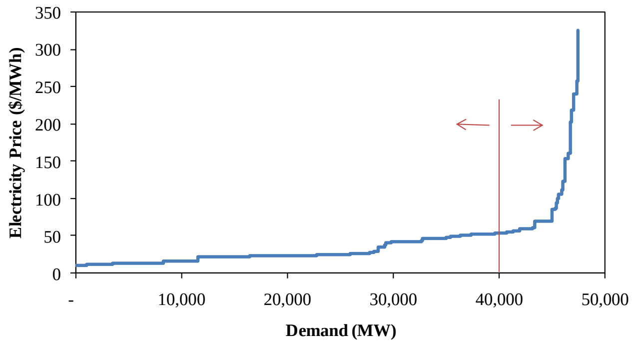


Figure 12. Sample electricity supply curve

Since the commercial sector is not the only electricity consumer, we assume that the residential, industrial, and transportation sectors in total consume 65% of the total regional electricity [1]. This portion is modeled as a fixed base demand curve below the fluctuating demand of commercial buildings. For the baseline case in which no building agent takes demand reduction actions, the regional electricity demand profile is calculated as shown in Fig. 13.

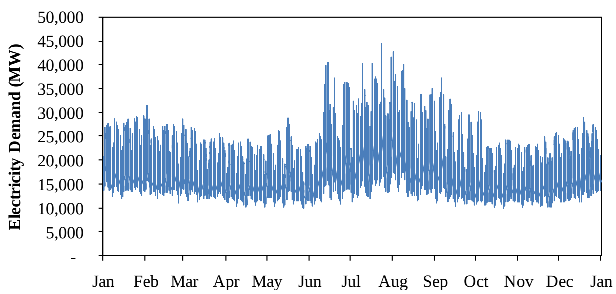


Figure 13. Estimated electricity load profile – baseline

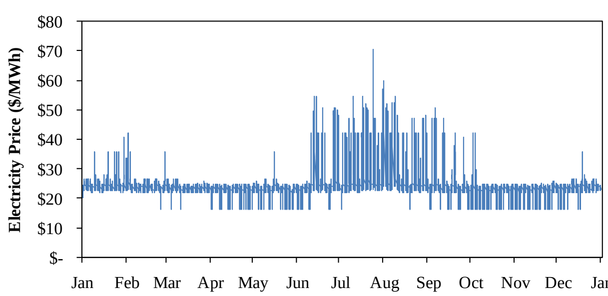


Figure 14. Estimated electricity price profile – baseline

In this case, the load reduction actions are applied to more building types. The example set of arrangements is listed in Table VIII.

TABLE VIII. AGENT LOAD-REDUCING ACTIONS AND ELECTRICITY PRICE

Demand Reduction Scenario	Agents Applied to	When the Power Price Is above	Action from Buildings
(a) Cooling set-point temperature	O, H, R, FE	$45/MWh	Increase set-point temp. by 2°C
(b) Heating set-point temperature	O, H, R, FE	$45/MWh	Decrease set-point by 2°C
(c) Lighting	O, S, R, E, FE	$45/MWh	Reduce lighting load by 30%
(d) Internal equipment	O, E	$45/MWh	Reduce internal equip. load by 30%

The simulation results are plotted in Fig. 15, which compares the hourly load profile with and without load reduction actions. Small decreases in electricity demand appear during the middle of each day, when the electricity price is high. All the demand reduction actions have led to a decrease in annual regional electricity consumption (including all the sectors) of about 0.2%.

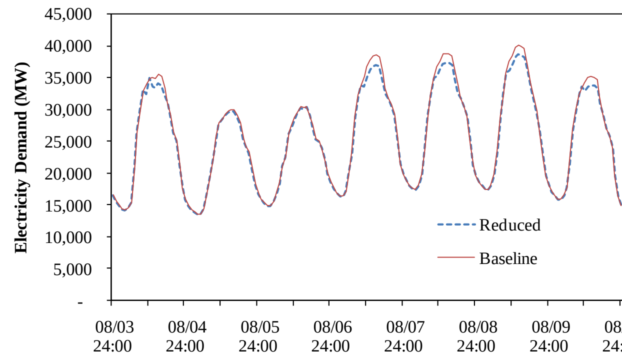


Figure 15. Commercial building stock electricity demand before and after reduction actions, Aug. 4th through 11th

However, on the price side, these actions shaved the electricity price profile (compare Fig. 16 and 14). The annual maximum market price dropped from ~$70 to ~$60/MWh. Although in this test case simulation, only part of the building agents took action, the changes in load and price profiles demonstrate the impact of commercial buildings on the smart grid.

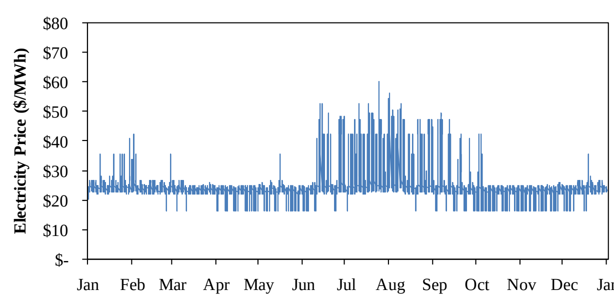


Figure 16. Estimated electricity price profile– after load reduction

V. CONCLUSION AND FUTURE WORK

This paper discusses a preliminary study on simulating commercial buildings as consumer agents that interact with the electricity market. A bottom-up building agent model, together with a building stock simulation framework, is proposed. By using a macro-model of the electricity supply curve, the dynamic pricing process is also modeled. This is the first attempt to address the role of consumers in a "white-box" and hourly approach. Two test cases demonstrate the capabilities of the proposed framework to help in large-scale smart grid simulations.

In the future, we intend to apply the prototype in a power grid simulation tool, thus providing more detailed options for modeling the market pricing mechanism. In addition, how to determine and judge the quality of representative buildings for each agent deserves further research. A statistical calibration method should be developed to determine and evaluate the input parameters that highly reflect the nature of the building stock, with respect to the inherent uncertainty in consumption simulations.

ACKNOWLEDGMENTS

The authors appreciate the help they received from Dick van Dijk and Jean-Robert Millet, two ISO 13790 developers, in implementing the simple hourly building energy method. This work was supported by the U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, Building Technologies Program, under contract DE-AC02-06CH11357.

REFERENCES

[1] IA, "Annual Energy Outlook 2010," 2009.

[2] J. D. Ryan and A. Nicholls, "Commercial building R&D program multi-year planning: opportunities and challenges," in *Proceedings of the ACEEE Summer Study on Energy Efficiency in Buildings*, Washington, DC., 2004.

[3] TIAX, "Energy Impact of Commercial Building Controls and Performance Diagnostics," 2005.

[4] Federal Energy Regulatory Commission, "A national assessment of demand response potential," Washington, D.C.2008.

[5] L. Exarchakos, *et al.*, "Modelling electricity storage systems management under the invluence of demand-side management programs," *International Journal of Energy Research*, vol. 33, pp. 62-76, 2009.

[6] K. H. v. Dam, *et al.*, "Agent-based control of distributed electricity generation with micro combined heat and power-cross-sectoral learning for process and infrastructure engineers," *Computers & Chemical Engineering*, vol. 32, pp. 205-217, 2008.

[7] P. Vytelingum, *et al.*, "Agent-based micro-storage management for the smart grid," in *9th Internaional Conference on Autonomous Agents and Multi-Agent Systems*, Toronto, Canada, 2010.

[8] ISO, "13790:2008," in Energy performance of buildings - Calculation of energy use for space heating and cooling, ed, 2008.

[9] DOE. (2010, July 27). *EnergyPlus (5.0 ed.)*. Available: http://apps1.eere.energy.gov/buildings/energyplus/

[10] J.-R. Millet, "The simple hourly method of prEN 13790: a dynamic method for the future," in *Chima 2007 WellBeing Indoors*, Helsinki, Finland, 2007.

[11] T. R. Nielsen, "Simple tool to evaluate energy demand and indoor environment in the early stages of building design," *Solar Energy*, vol. 78, pp. 73–83, 2005.

[12] EIA. (2006, *2003 Commercial Buildings Energy Consumption Survey (CBECS)*. Available: http://www.eia.doe.gov/emeu/cbecs/contents.html

[13] DOE. (2009, *Commercial Reference Buildings (version 1.2_4.0 ed.)*. Available: http://www1.eere.energy.gov/buildings/commercial_initiative/reference_buildings.html

[14] M. Kavgic, *et al.*, "A review of bottom-up building stock models for energy consumption in the residential sector," *Building and Environment*, vol. 45, pp. 1683-1697, 2010.

[15] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniues," *Renewable and Sustainable Energy Reviews*, vol. 13, pp. 1819-1835, 2009.

[16] Y. Yamaguchi and Y. Shimoda, "Database and Simulation Model Development for Modelling the Energy Use of Non-Residential Buildings," in *Building Simulation 2009*, Glasgow, Scotland, 2009.

[17] B. Griffith, *et al.*, "Methodology for Modeling Building Energy Performance across the Commercial Sector," National Renewable Energy Laboratory, U.S. Department of Energy, Technical Report2008.